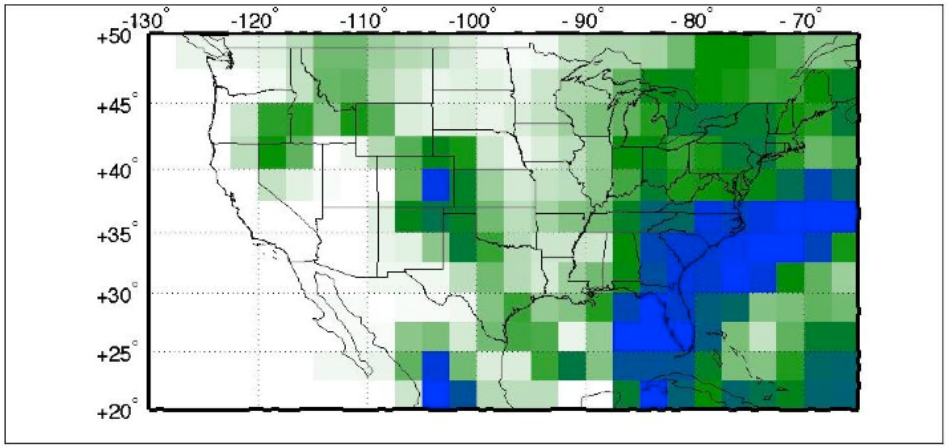
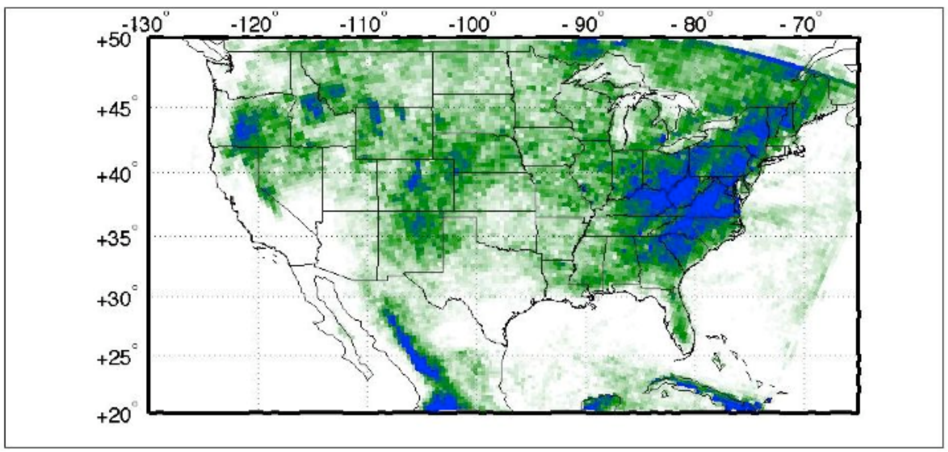
How is Climate Downscaling Data Produced? Sausage Making Meeting





Francina Dominguez
Seshadri Rajagopal
Christopher Castro
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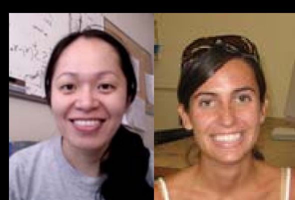
Collaborative Climate Workshop Series: Intermediate Activities

April 28, 2010

The structure of our talk…

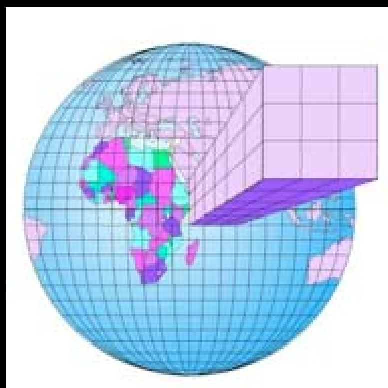
F. Dominguez: Introduction and overview of statistical downscaling results

C. Castro: Overview of dynamical downscaling and current projects.

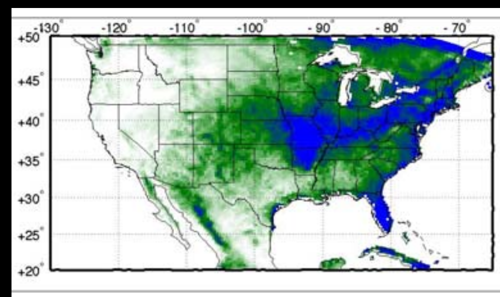


F. Dominguez, H. Chang, B. Ciancarelli: Dynamical Downscaling results and initial analyses

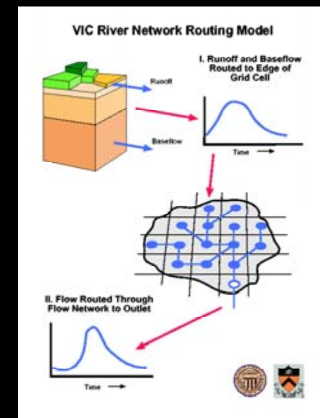
Our goal is to downscale climate model data to an appropriate resolution for hydrological applications.



1. We rely on General Circulation Models (GCMs) to estimate future climate variables

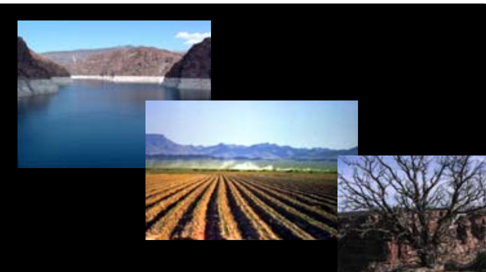


2. These projections are downscaled using either statistical or dynamical methods



3. Downscaled atmospheric fields force the VIC hydrologic model.

4. The outcomes will be used to generate water management data for drought planning, scenarios, modeling, agricultural, tribal activities, etc.



There are basically two approaches to downscale coupled climate model projections :

Statistical Downscaling

Dynamical Downscaling

There are basically two approaches to downscale coupled climate model projections :

Statistical Downscaling

These methods assume a relationship between large-scale atmospheric variables (predictors) and local climate variables (predictands).

- **Pro : Cheap and computationally efficient.**
- **Pro : Can use many different scenarios, model runs.**
- **Pro : Easily transferable to other regions.**

- **Con : Requires long and reliable observation data.**
- **Con : Depends on choice of predictors.**
- **Con : Assumes stationarity of predictor-predictand relationship.**
- **Con : Cannot account for feedbacks.**

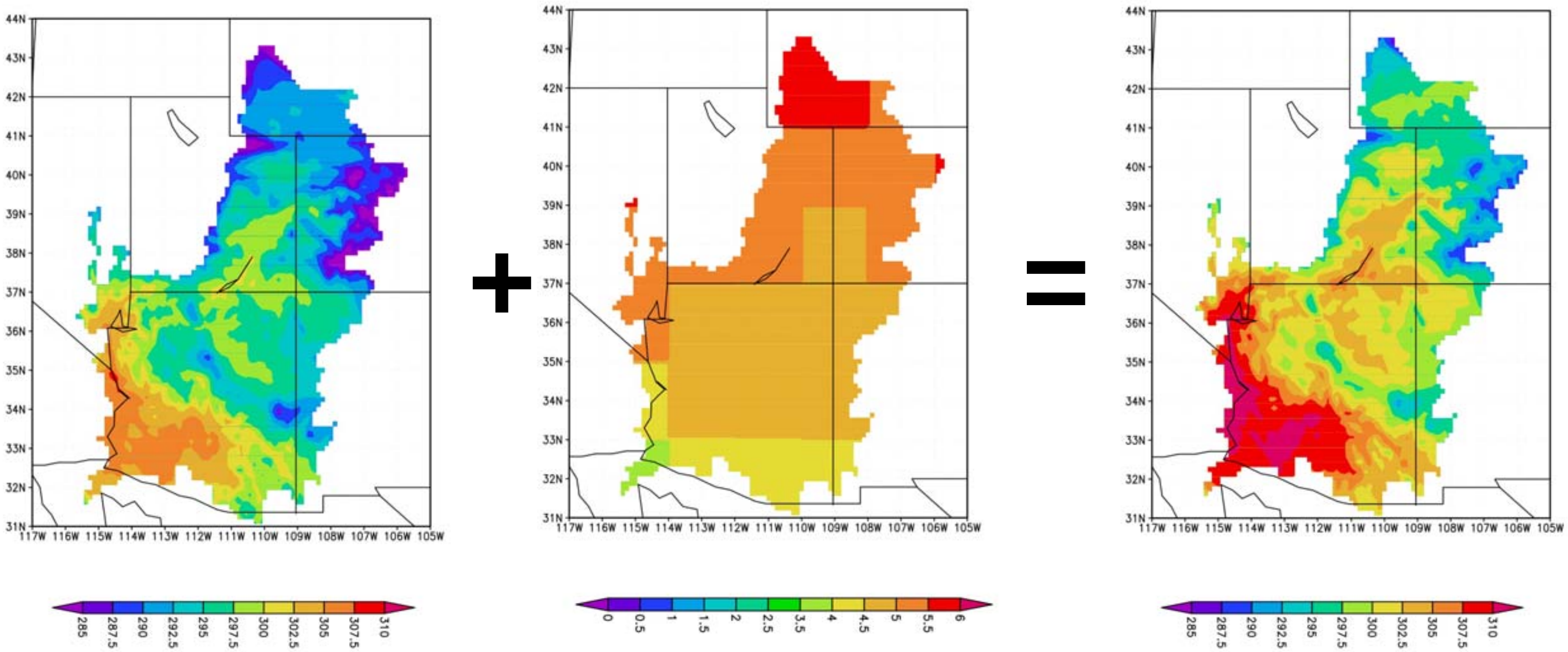
Perturbation methods are probably the simplest you can use.

observational projection

GCM

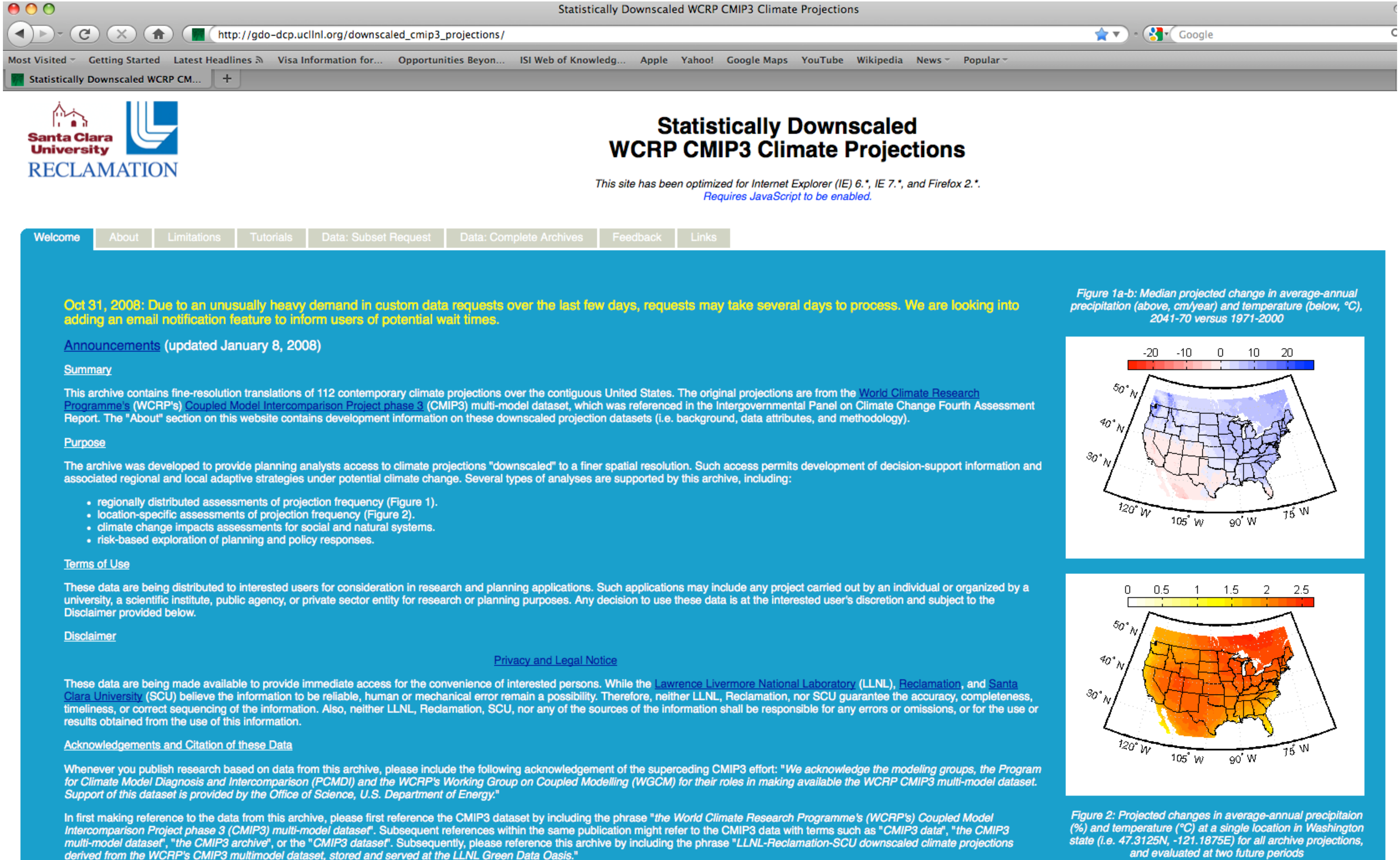
Downscaled projection

$T_{HR\_MEAN}(m)$ + $T_{ANOM\_PROJ}(m,e)$ = $T_{HR\_PROJ}(m,e)$



LLNL-Reclamation-SCU downscaled climate projections derived from the WCRP's CMIP3 multimodel dataset, stored and served at the LLNL Green Data Oasis is done using this technique (bias corrected).

Statistical Downscaling



Statistically Downscaled WCRP CMIP3 Climate Projections

http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/

Santa Clara University RECLAMATION

Statistically Downscaled
WCRP CMIP3 Climate Projections

This site has been optimized for Internet Explorer (IE) 6., IE 7.*, and Firefox 2.*.*
Requires JavaScript to be enabled.

Welcome | About | Limitations | Tutorials | Data: Subset Request | Data: Complete Archives | Feedback | Links

Oct 31, 2008: Due to an unusually heavy demand in custom data requests over the last few days, requests may take several days to process. We are looking into adding an email notification feature to inform users of potential wait times.

Announcements (updated January 8, 2008)

Summary

This archive contains fine-resolution translations of 112 contemporary climate projections over the contiguous United States. The original projections are from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset, which was referenced in the Intergovernmental Panel on Climate Change Fourth Assessment Report. The "About" section on this website contains development information on these downscaled projection datasets (i.e. background, data attributes, and methodology).

Purpose

The archive was developed to provide planning analysts access to climate projections "downscaled" to a finer spatial resolution. Such access permits development of decision-support information and associated regional and local adaptive strategies under potential climate change. Several types of analyses are supported by this archive, including:

- regionally distributed assessments of projection frequency (Figure 1).
- location-specific assessments of projection frequency (Figure 2).
- climate change impacts assessments for social and natural systems.
- risk-based exploration of planning and policy responses.

Terms of Use

These data are being distributed to interested users for consideration in research and planning applications. Such applications may include any project carried out by an individual or organized by a university, a scientific institute, public agency, or private sector entity for research or planning purposes. Any decision to use these data is at the interested user's discretion and subject to the Disclaimer provided below.

Disclaimer

Privacy and Legal Notice

These data are being made available to provide immediate access for the convenience of interested persons. While the Lawrence Livermore National Laboratory (LLNL), Reclamation, and Santa Clara University (SCU) believe the information to be reliable, human or mechanical error remain a possibility. Therefore, neither LLNL, Reclamation, nor SCU guarantee the accuracy, completeness, timeliness, or correct sequencing of the information. Also, neither LLNL, Reclamation, SCU, nor any of the sources of the information shall be responsible for any errors or omissions, or for the use or results obtained from the use of this information.

Acknowledgements and Citation of these Data

Whenever you publish research based on data from this archive, please include the following acknowledgement of the superceding CMIP3 effort: "*We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy.*"

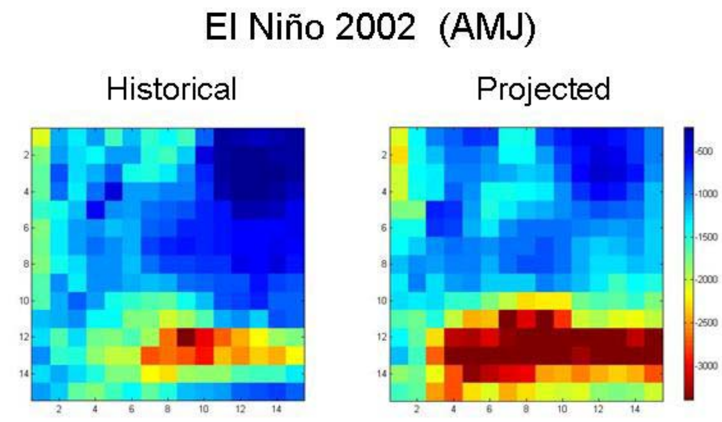
In first making reference to the data from this archive, please first reference the CMIP3 dataset by including the phrase "*the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset*". Subsequent references within the same publication might refer to the CMIP3 data with terms such as "*CMIP3 data*", "*the CMIP3 multi-model dataset*", "*the CMIP3 archive*", or the "*CMIP3 dataset*". Subsequently, please reference this archive by including the phrase "*LLNL-Reclamation-SCU downscaled climate projections derived from the WCRP's CMIP3 multimodel dataset, stored and served at the LLNL Green Data Oasis.*"

Figure 1a-b: Median projected change in average-annual precipitation (above, cm/year) and temperature (below, °C), 2041-70 versus 1971-2000

Figure 2: Projected changes in average-annual precipitaion (%) and temperature (°C) at a single location in Washington state (i.e. 47.3125N, -121.1875E) for all archive projections, and evaluated at two future periods

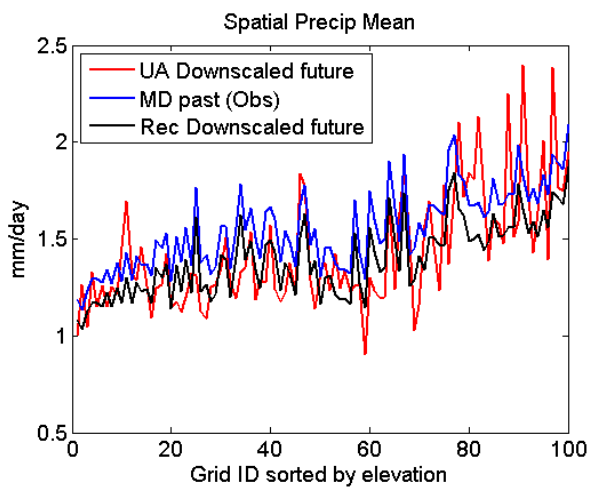
AKA: "Reclamation Data"

UofA developed a statistical method that accounts for climate oscillations.



Cañon et al. 2009

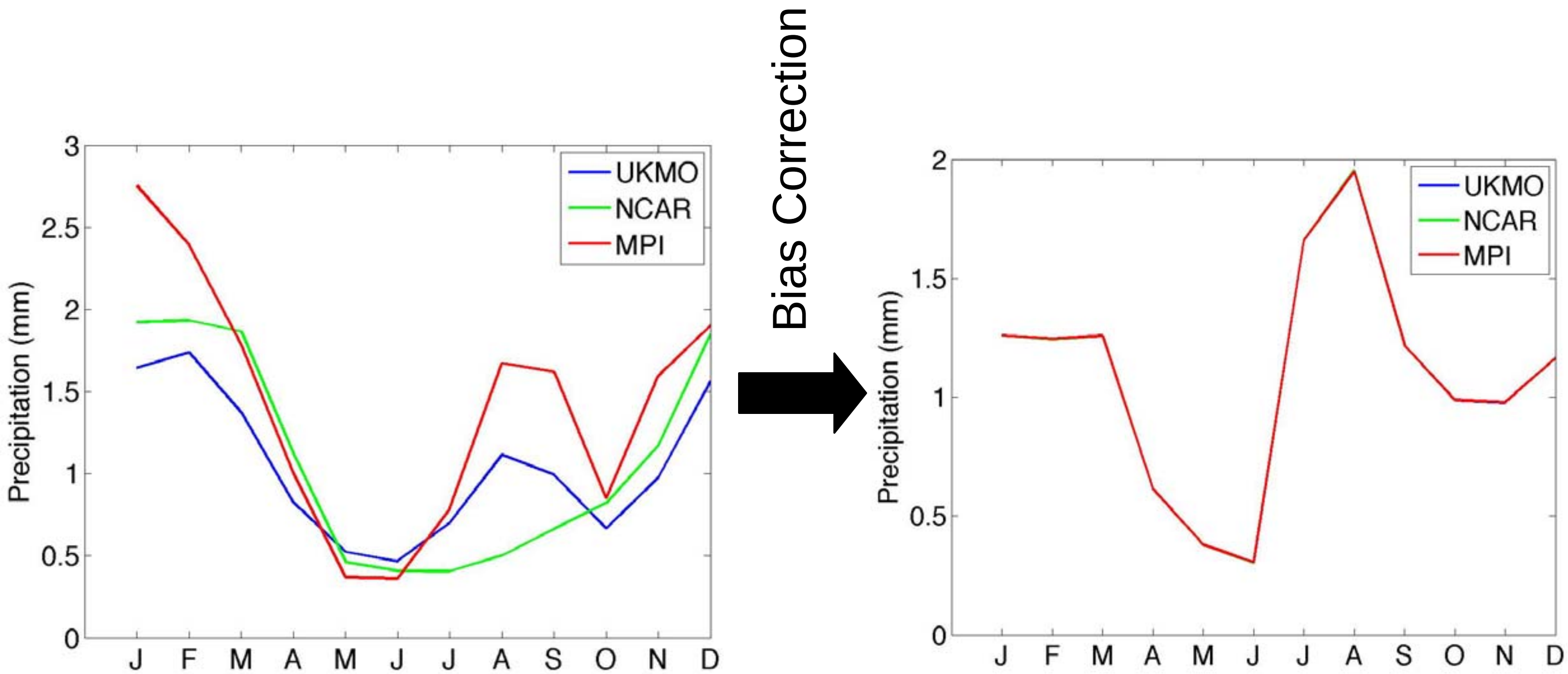
When compared to the Reclamation method, it yielded similar results, both forcing and VIC output



Rajagopal et al. 2009

We decided use the Reclamation data, because of the availability of different models/scenarios.

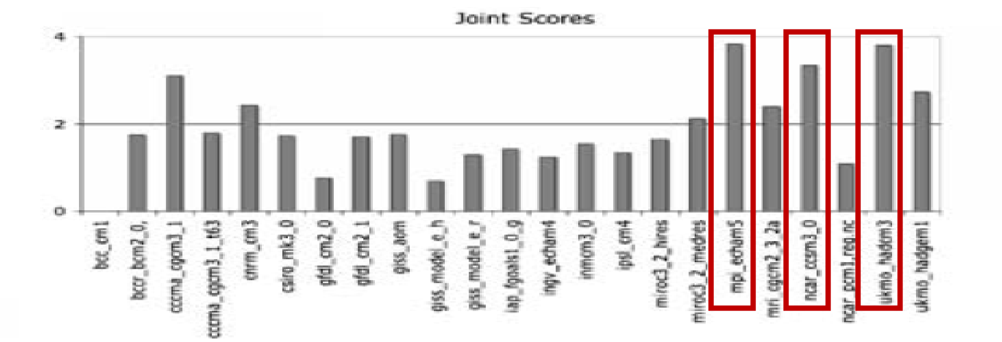
It is important to clarify that the Reclamation Data is Bias Corrected, so the observed climatological mean is matched in the historical data.

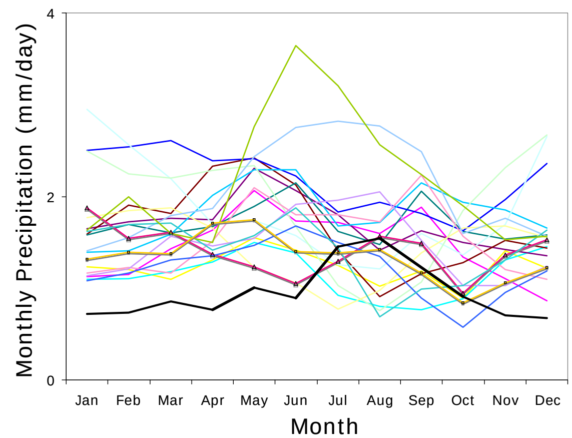


Raw GCM climatology for the three selected models (1950-2000)

“Reclamation” statistically downscaled climatology (1950-2000)

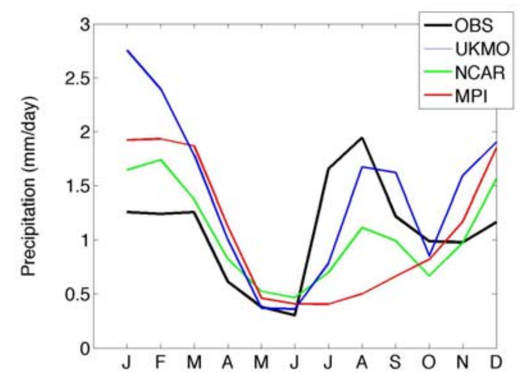
We ranked the IPCC-AR4 models based on their similarity with historical data and convergence in the future - for the Southwest Region.





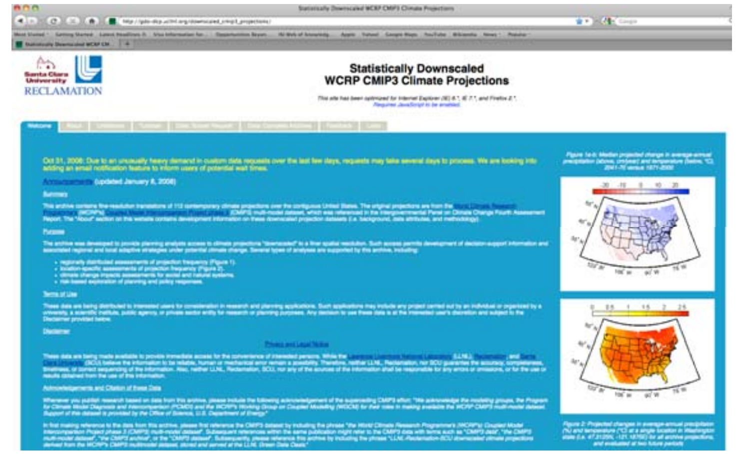
Climatology Southwestern US

The ukmo-hadcm3, mpi-echam5 and ncar-ccsm3 ranked highest among all models (Gleckler et al. 2008 found ukmo and mpi among the best as well).

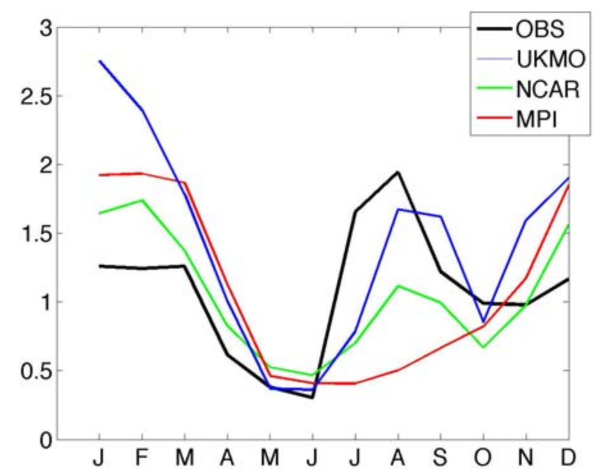


Climatology Salt-Verde Basin

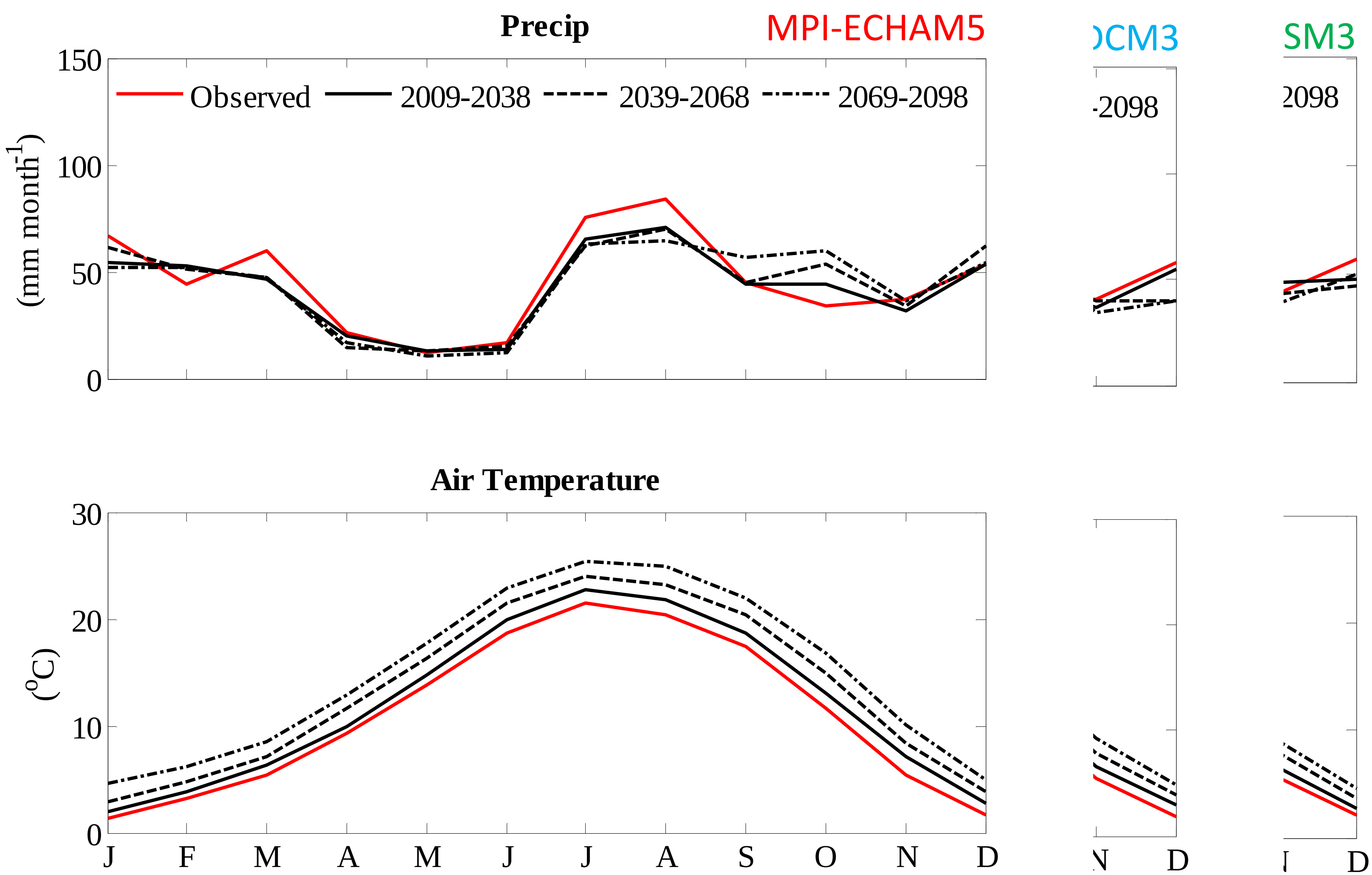
In summary, we use the "Reclamation" statistical downscaling to force VIC. This data is bias corrected.



We use data from three selected GCMs: the ukmo_hadcm3, ncar_ccsm3 and mpi_echam5 and three emission scenarios.

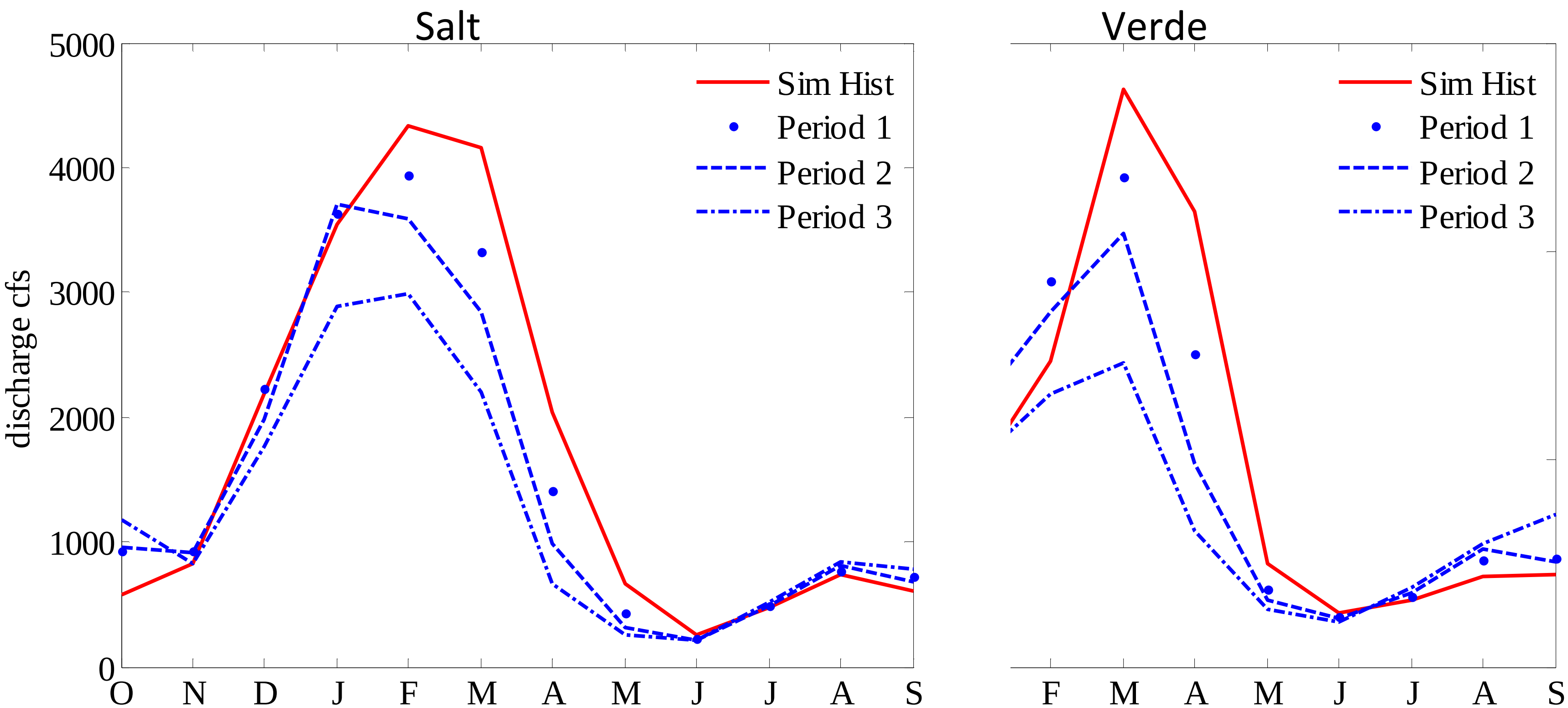


The three selected models all show increase in temperature and different trends in precip.



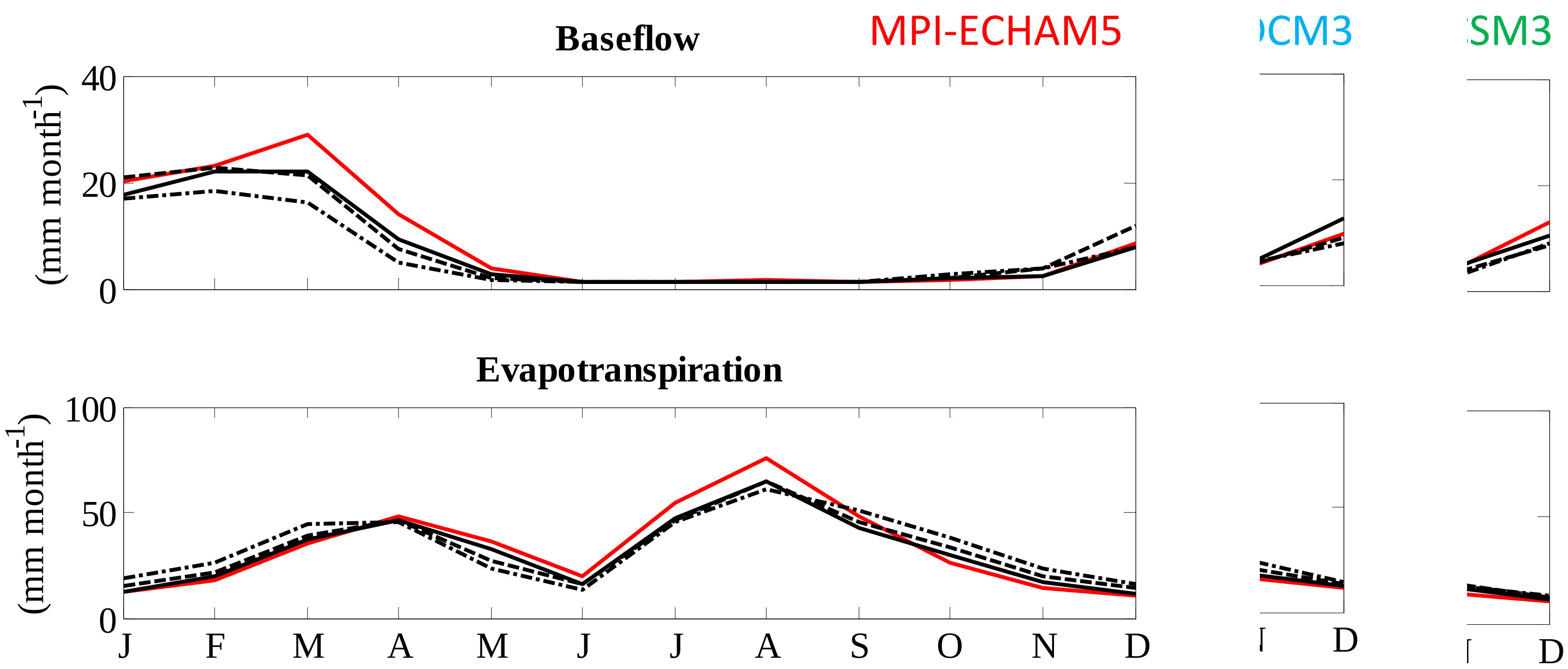
Rajagopal et al. 2010

All model runs show a decrease in cool season streamflow.



Rajagopal et al. 2010

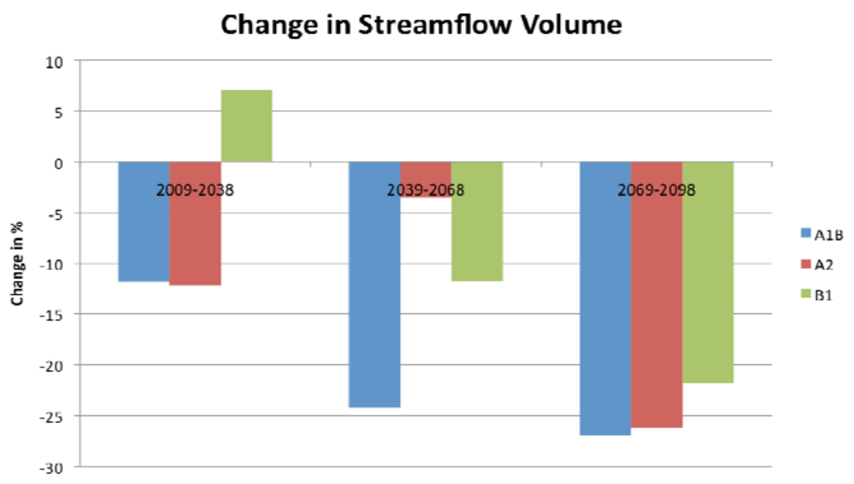
Slow flow (called Baseflow in VIC) decreases, while ET depends on precipitation changes.



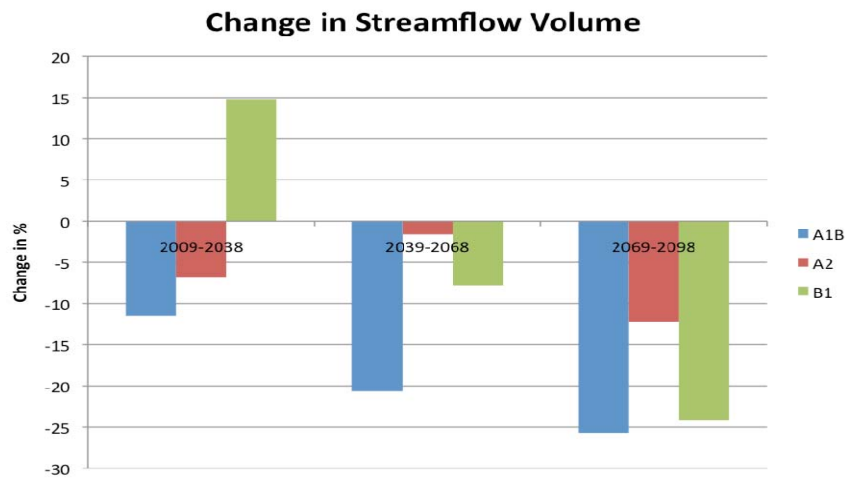
Rajagopal et al. 2010

In summary, both the Salt and Verde show a future decrease in streamflow.

Salt River Basin



Verde River Basin



The second downscaling approach is dynamical downscaling.

Dynamical Downscaling

- Pro : Produces responses based on physically consistent processes.
- Pro : Captures feedbacks.
- Pro : Can model changes that have never been observed in historical record.
- Pro : Useful where topographic controls are important.

- Con : Requires significant computational power.
- Con : Limited amounts of models / runs / timescales.
- Con : Dependant on GCM boundary forcing.
- Con : Problems with drifting of large-scale climate.


Regional Climate
Modeling Team

Dynamical Downscaling

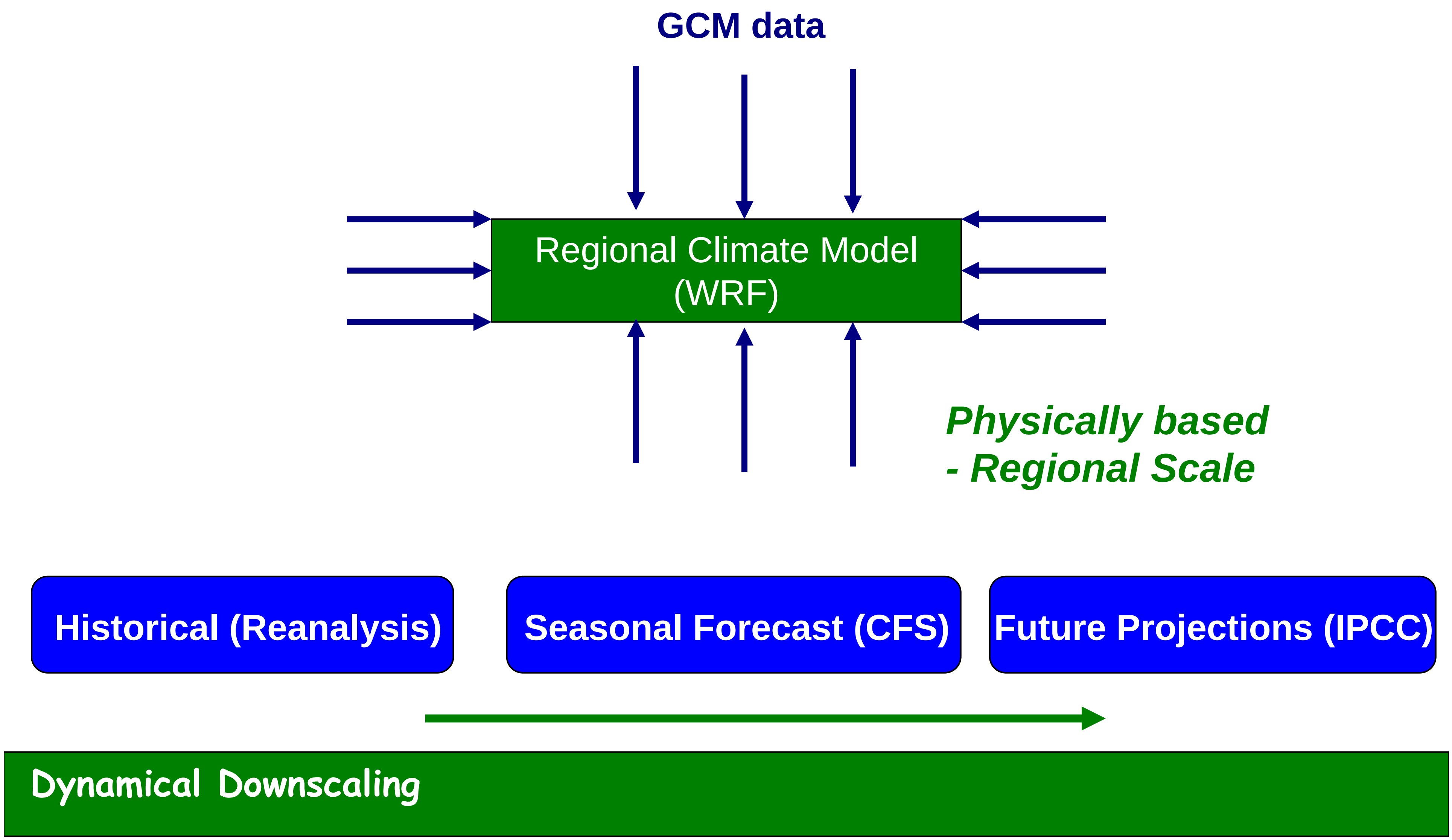
<u>Definition</u>: *Use some kind of numerical model to generate finer-resolution information from courser resolution information. For the atmosphere, this is a limited area model.*

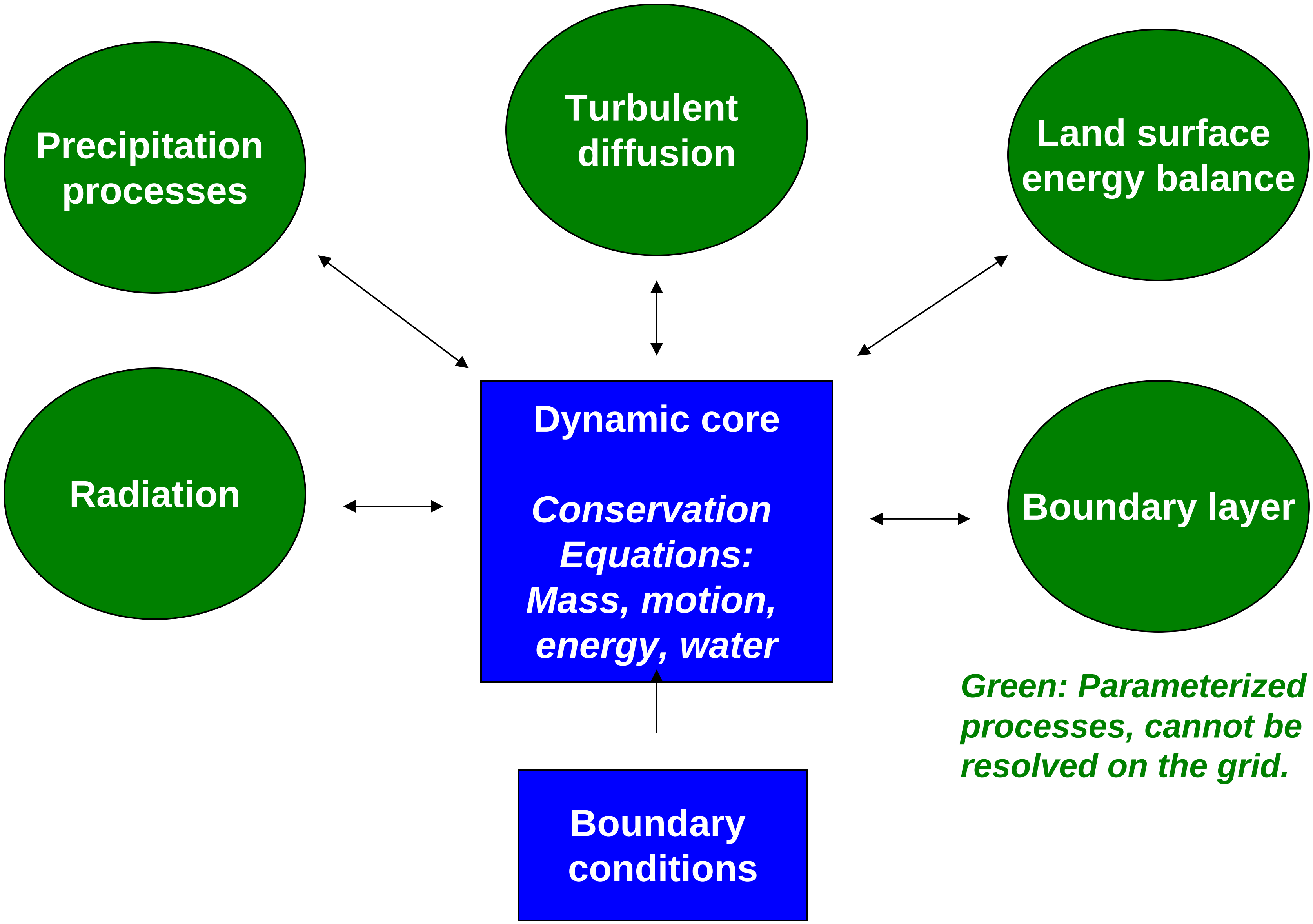
Implicit assumption: A finer resolution and/or improved model physics (parameterizations) gives a "better" representation of weather and climate than the driving coarser resolution model (i.e. GCM).

"Better" may = more fidelity with observations and/or improved representation of physical processes

If this is not satisfied, you're wasting money in terms of computer time to generate simulations and labor to analyze the results!!

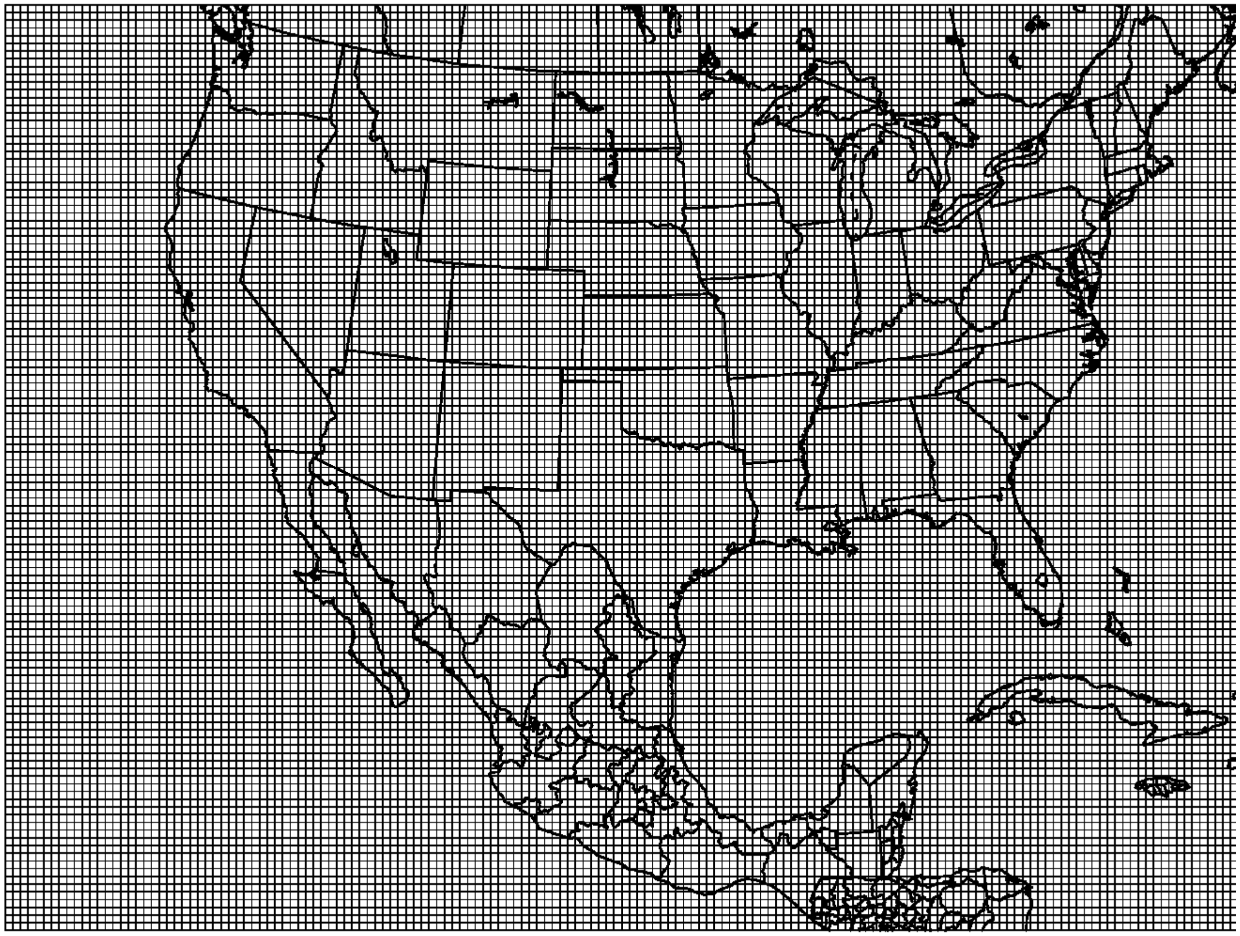
Use the regional model as a "magnifying lens" to create higher resolution data…



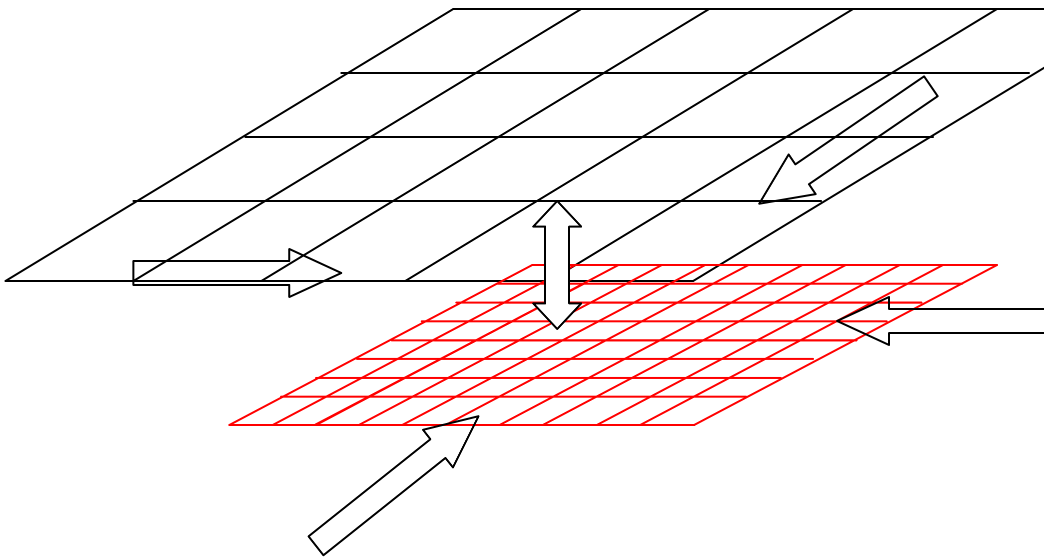


Dynamical Downscaling

Regional Model Grid (35km grid spacing)



GCM not only provides lateral boundary conditions. It is also used to force the interior of the model…

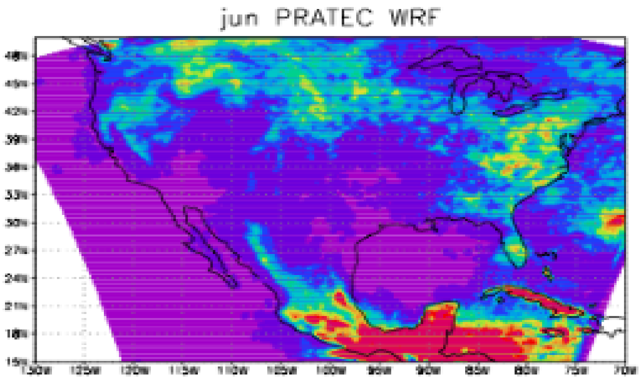


This helps maintain the appropriate variability in model fields at upper levels and at large scales.

WRF-simulated precipitation with and without interior forcing

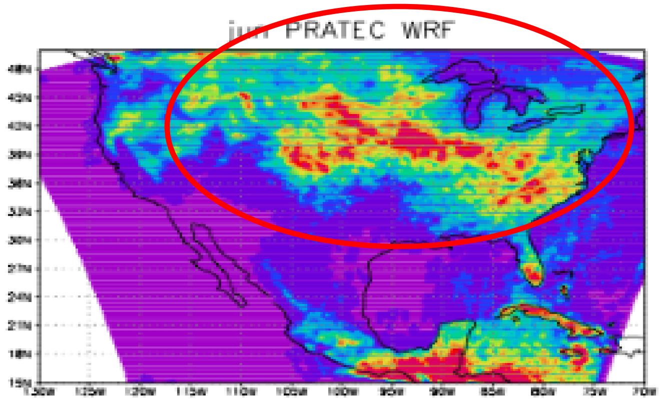
June 1993: Central US flood

WRF
Lateral
boundary
nudging only



Region of intense observed precipitation

WRF
Spectral
nudging



mm/day

We are performing different types of Dynamical Downscaling at the UofA using WRF:

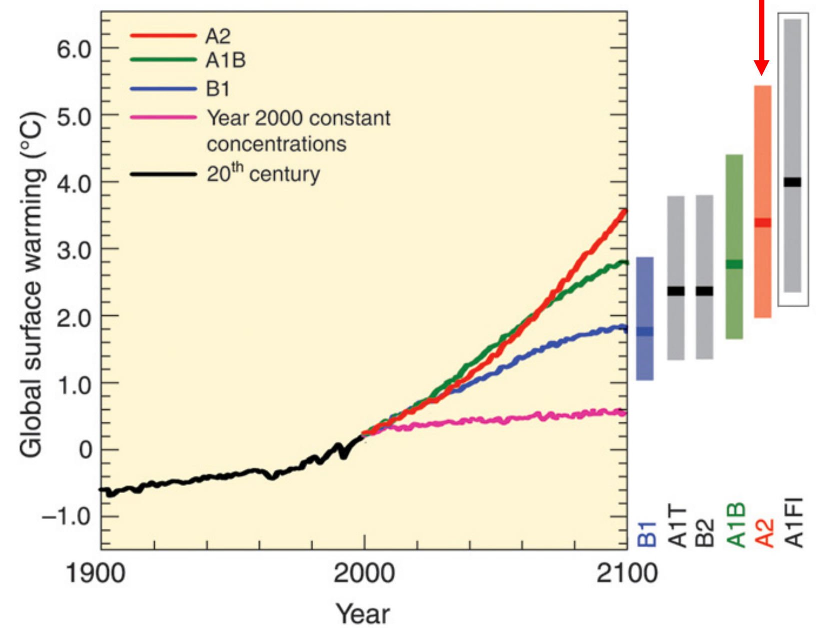
Historical (Reanalysis)	1979-2000	Done this spring
Seasonal Forecast (CFS)	1982-2000	Done Aug. 09
Three IPCC AR4 models for A2 emission scenario	1968-2081	One model done as of this April

Future Projections (IPCC) Using HadCM3

1968-2079

Science Question: How will climate in the Southwestern United States change due to global warming?

Methodology: We use WRF with spectral nudging to downscale 113 (1968-2081) years of SRES A2 data from three "well performing" IPCC models.



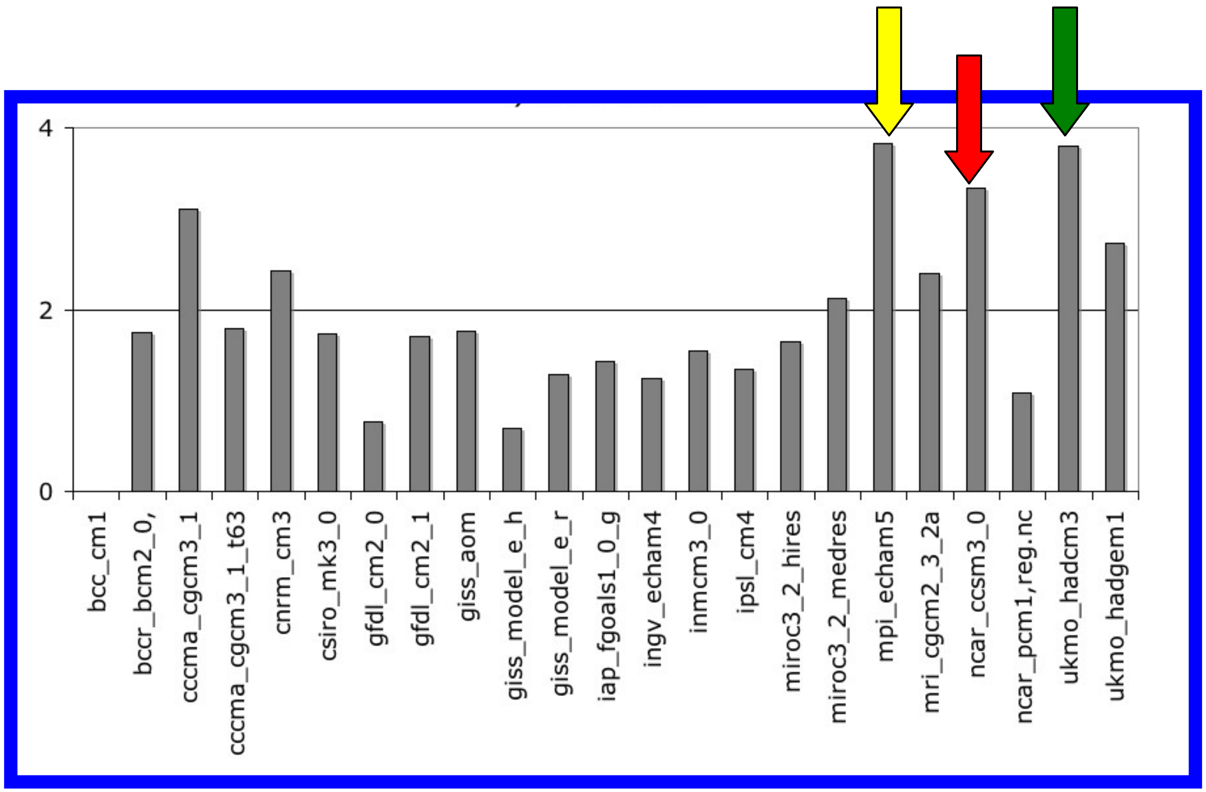
Dynamical Downscaling

We chose to downscale the **three well performing IPCC AR4 models** that best represent the historical precipitation and temperature climatology in the Southwest and upper atmosphere circulation patterns in the Northern Hemisphere. ***These also have different GCM precipitation projections for Arizona (i.e. include "wet" and "dry" models)***

HadCM3: Completely done

MPI Echam: GCM data being obtained

CCSM: Will get these data soon



Dominguez et al (2009)

While statistically downscaled data will generally give us two variables (P and T), dynamical downscaling gives us approx. 90. At a 6hry resolution.

Winds (different levels), temperature, humidity, ET, potET, SWE, snow depth, soil moisture …

RCM variables being provided to the hydrologic modeling team

2m Surface air temperature

10 m Surface winds

Relative and absolute humidity

Precipitation

Short and longwave radiation

Snow water equivalent

Snow depth

Higher confidence
Variables more dependent on dynamic core

Lower confidence
Variables more dependent on model parameterizations

Required resources for UA
dynamical downscaling activities

Salaries

Faculty (Castro, **Dominguez**), a **postdoctoral researcher**, graduate students, technical support
$100-200 K per year when fringe benefits included.

Computing equipment

Multiprocessor linux clusters, **RAID storage systems (10s of terrabytes),** local desktops, data interface?
$100-200 K for linux clusters (already covered through faculty startups, federal grants), $10-30 K for RAID systems, $5 K for workstations

Travel and publications

$5-10 K per year

Current partner funding from this project is contributing to funding highlighted items

Dynamical Downscaling IPCC data

The process of downscaling the UKMO-HadCM3 data involved several steps:

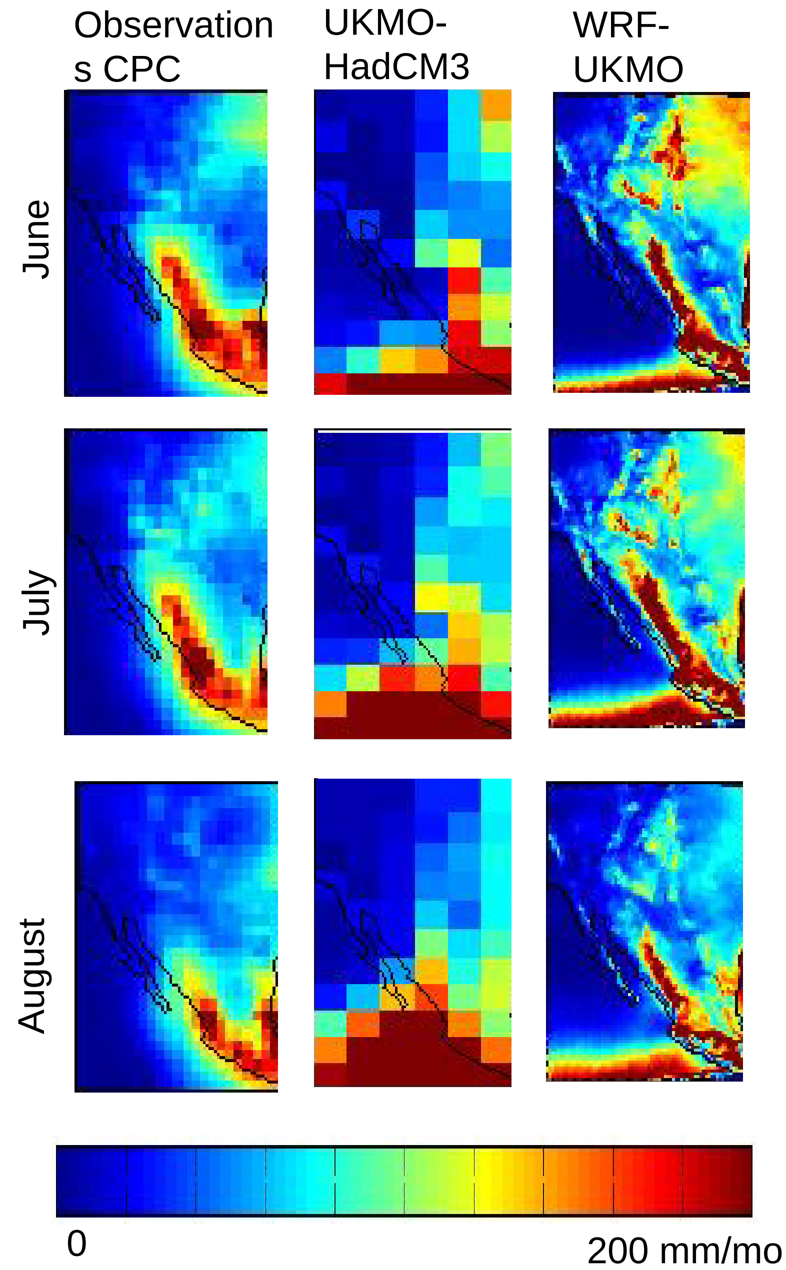
Feb 09

- Select the models to downscale consulting with stakeholders
- Obtain data at all 6-hrly temporal resolution and all the variables.
- Process the data to input into the regional climate model
- Modify the RCM for these types of simulations.
- "Nurse" the model run.

Using 128 processors

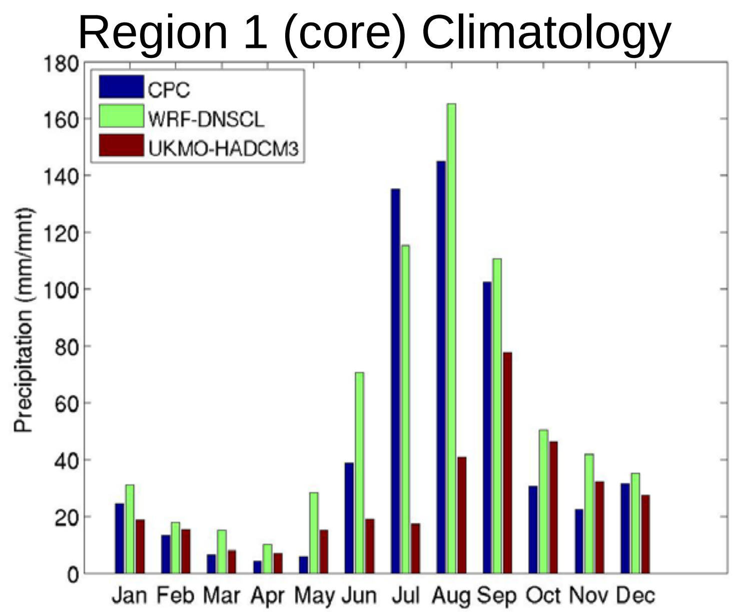
Preliminary analysis of results…

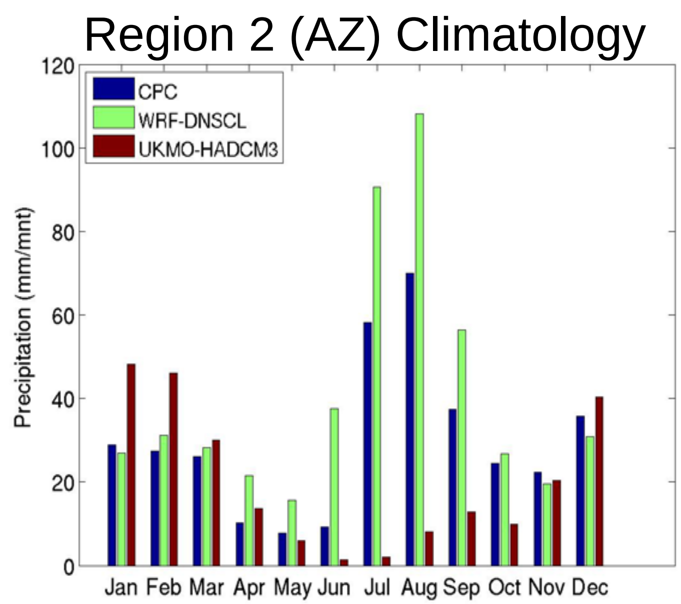
1968-2000 June July and August precipitation climatology of WRF downscaled UKMO-HadCM3 data show a much more realistic spatial representation of the North American Monsoon than the raw model.



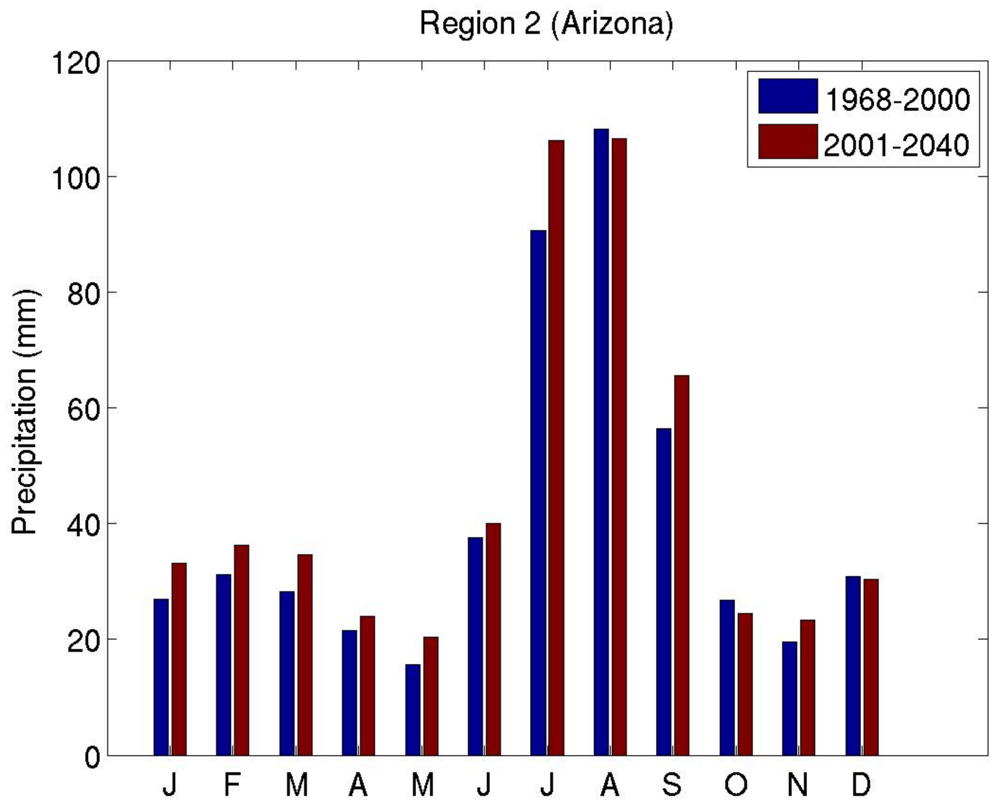
Preliminary analysis of results…

1968-2000 monthly climatology shows that WRF represents the timing and intensity of the Monsoon more realistically than the raw model.

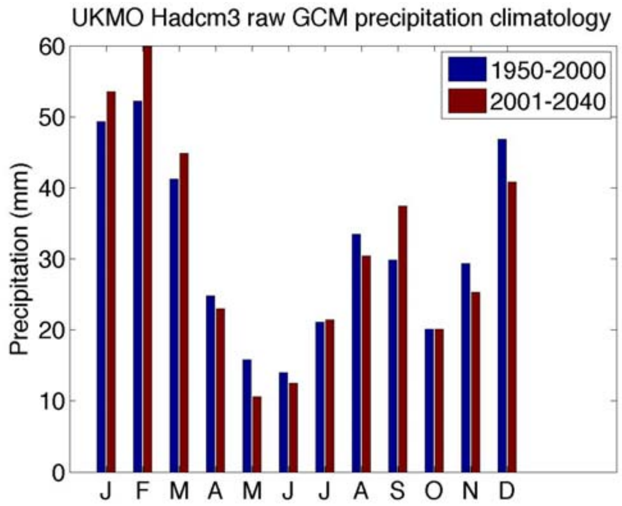




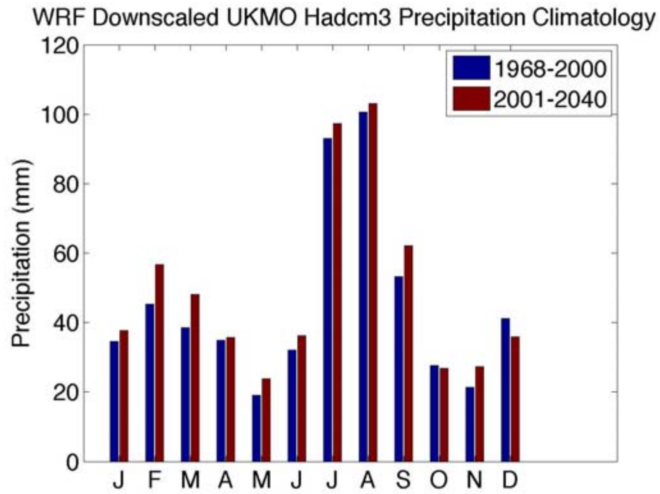
Preliminary results of future precipitation show that the 2001-2040 climatology has a generalized higher precipitation – Particularly in July, as compared to the 1968-2000 monthly climatology.



We believe the reason for these changes in precipitation can be summarized as follows (Salt-Verde Basin).

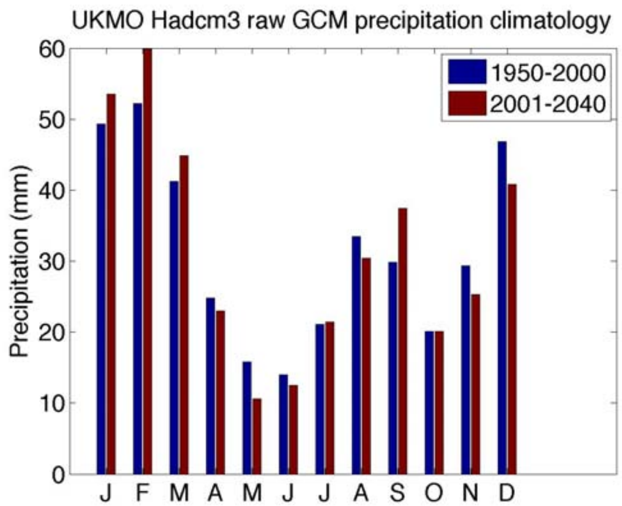


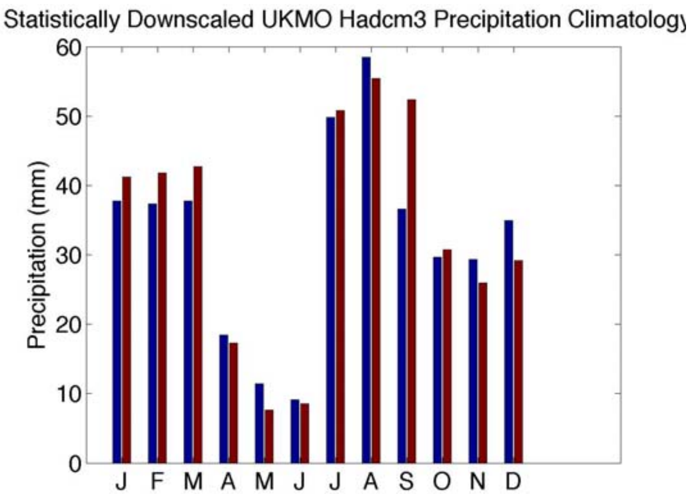
In the winter, dominated by large scale circulation, the raw GCM (UKMO) shows an increase in precipitation.

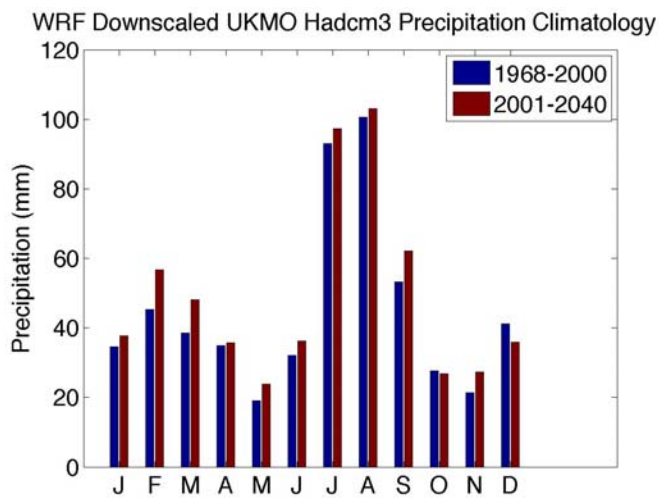


In addition to the winter increase, the RCM more realistically captures the summer rains (wet bias). The increase in global atmospheric moisture might be driving an increase in summer rain. This must be investigated.

To contrast with statistical downscaling

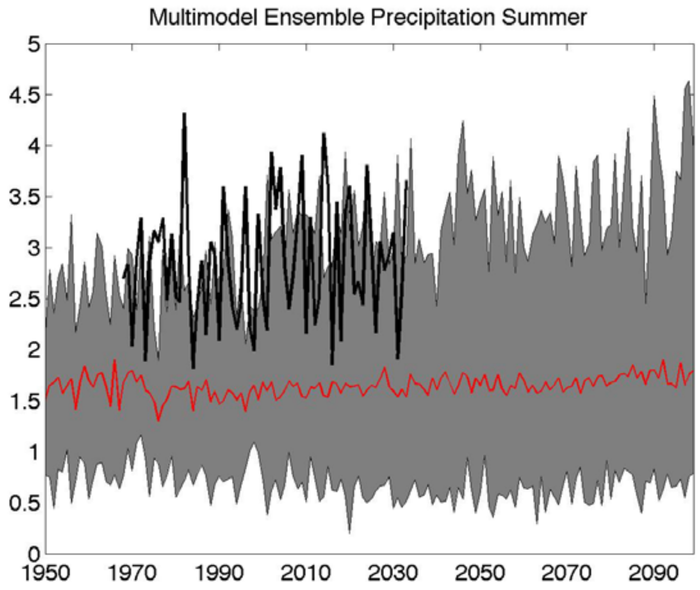


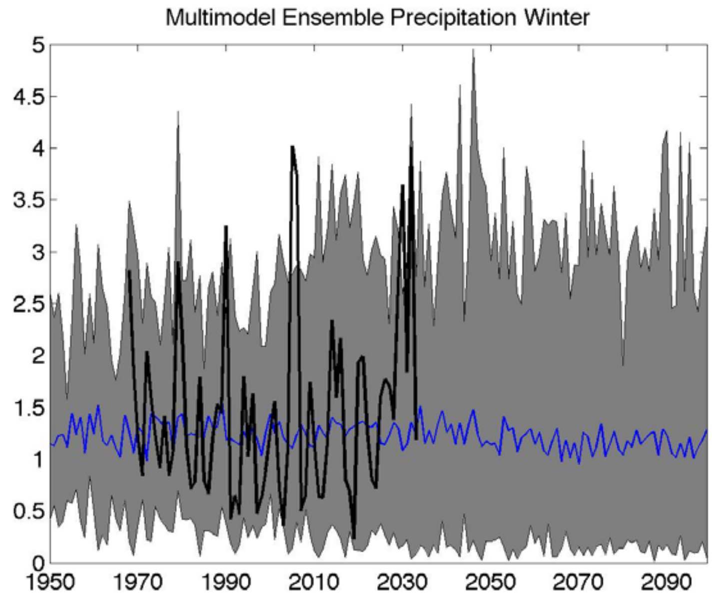




The statistical downscaling inherits the change in precipitation from the GCM and assigns a historical climatology. Consequently, it doesn't show any difference in the summer.

When comparing Dynamical Downscaling Results with (Bias Corrected) Statistical Downscaling, we see a wet bias in summer precipitation, and considerable variability in winter precipitation.

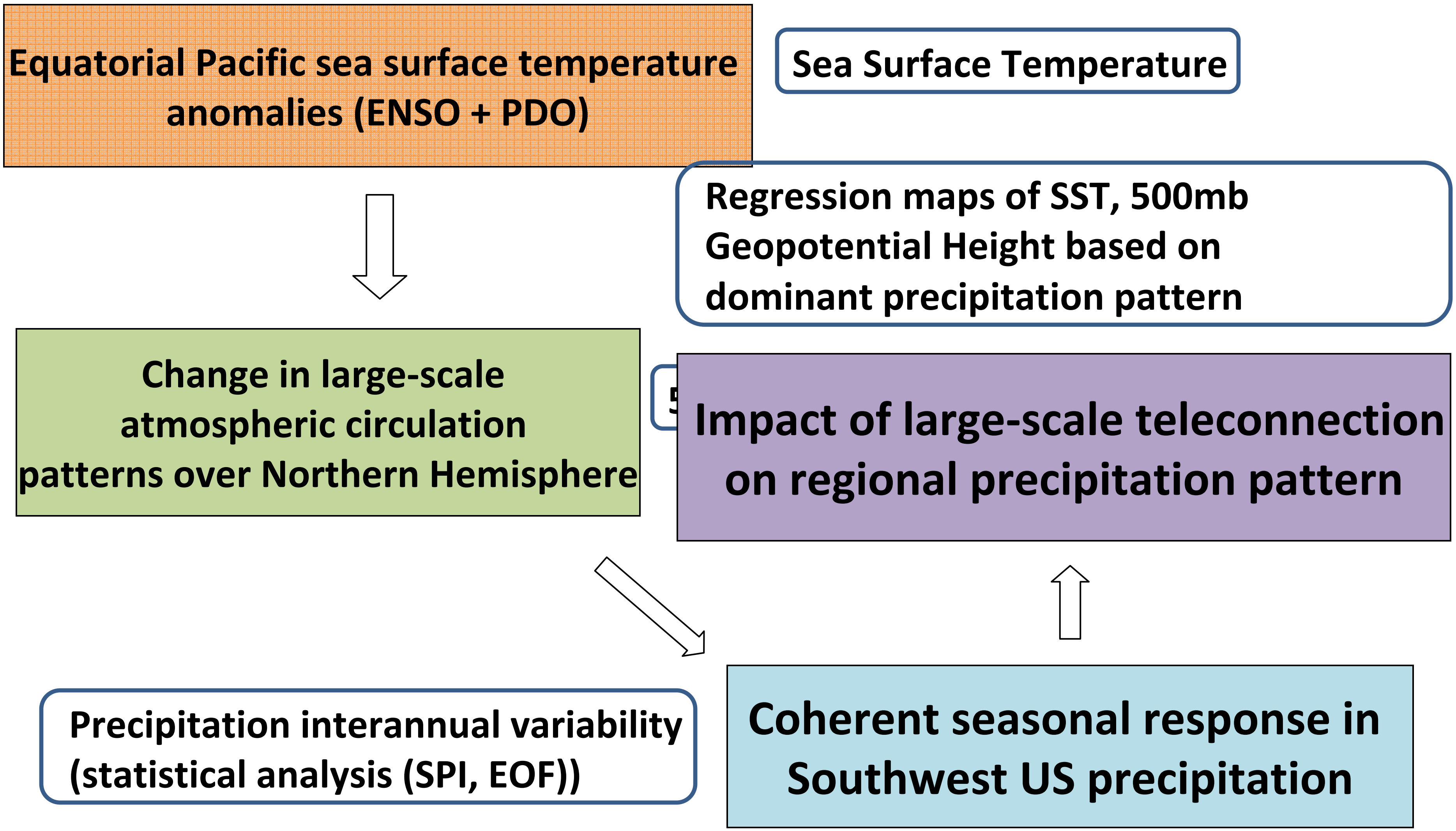




The hydrologic modeling team will speak about how they are dealing with the bias.

We have talked about the climatological analysis, now let’s look at the interannual variability…

Connections between seasonal precipitation variability and large scale teleconnections



Statistical analysis methods:

Precipitation normalization

- Standard Precipitation Index(SPI): Accounts for non-normal distribution of precipitation

Spatial pattern recognition

- Rotated Empirical Orthogonal Function Analysis(REOF)

Relationship of dominant modes of precipitation variability to large-scale forcing factors

- Regression Analysis between precipitation modes and SST, geopotential height

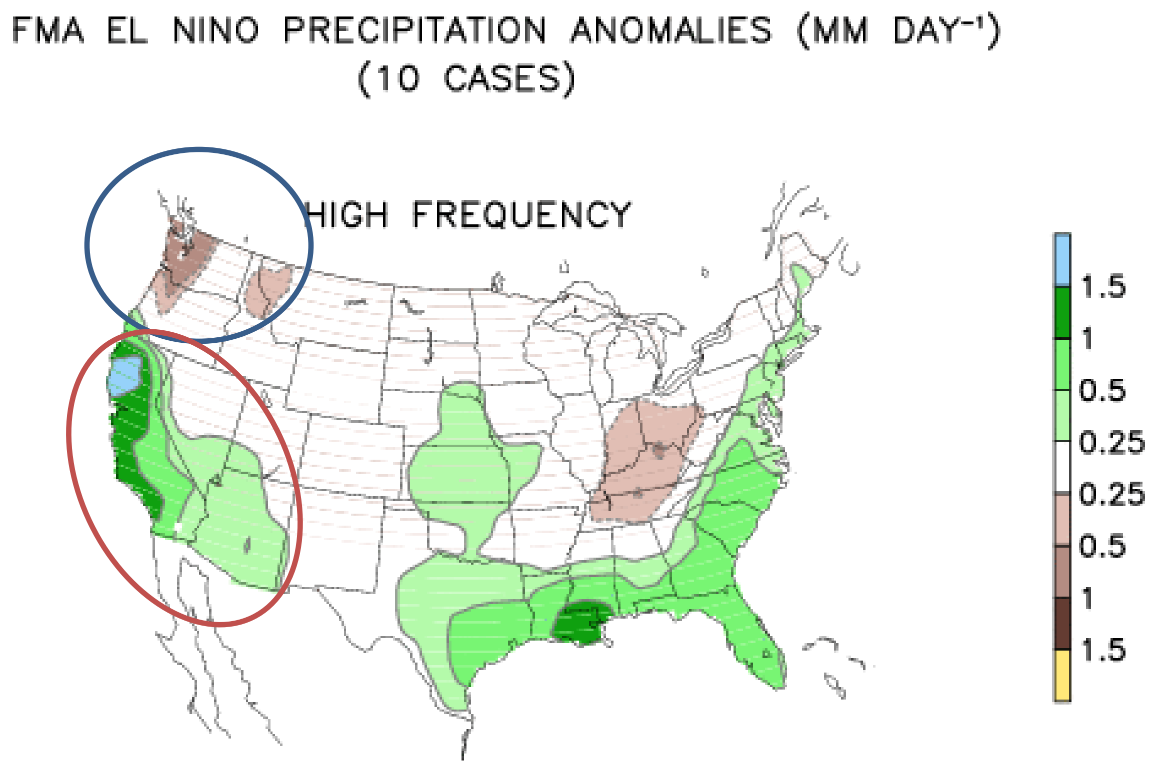
What we look for to assess natural variability in downscaled climate data

GCM: need to capture the SST forcing and associated large-scale circulation pattern

- RCM: need to capture the regional precipitation variability

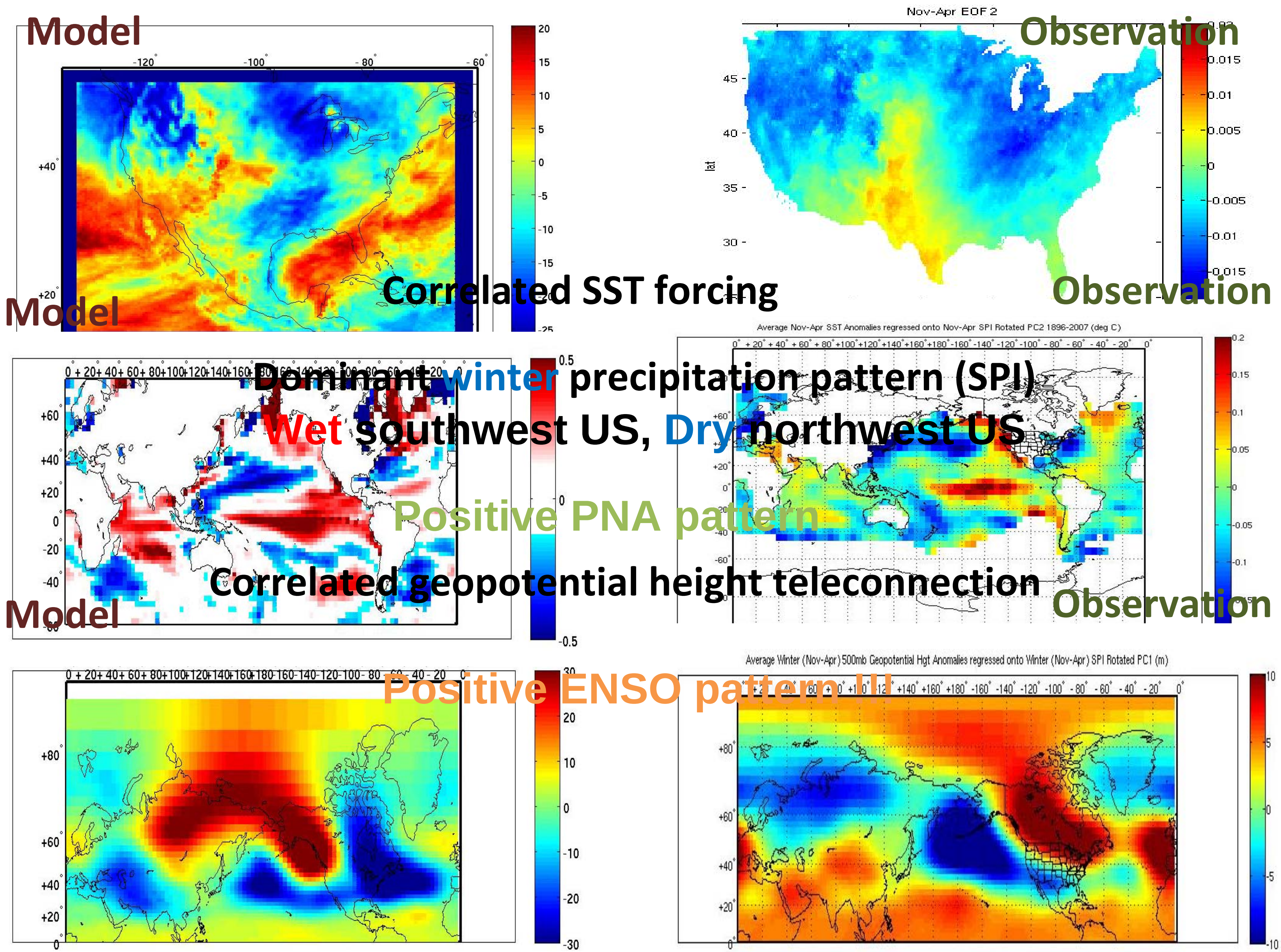
- Expectations for dynamically downscaled output:
  - Capture Pacific forced interannual variability, which must be seen in the dominant regional precipitation patterns, associated sea surface temperatures and large scale circulation

Dominant pattern of variability for winter season



Typical winter precipitation anomaly during El Nino year

Source: Climate Prediction Center


Model
Observation
Nov-Apr EOF 2
Dominant winter precipitation pattern (SPI)
Wet southwest US, Dry northwest US
Model
Observation
Correlated SST forcing
Average Nov-Apr SST Anomalies regressed onto Nov-Apr SPI Rotated PC2 1896-2007 (deg C)
Positive ENSO pattern !!!
Model
Observation
Correlated geopotential height teleconnection
Average Winter (Nov-Apr) 500mb Geopotential Hgt Anomalies regressed onto Winter (Nov-Apr) SPI Rotated PC1 (m)
Positive PNA pattern

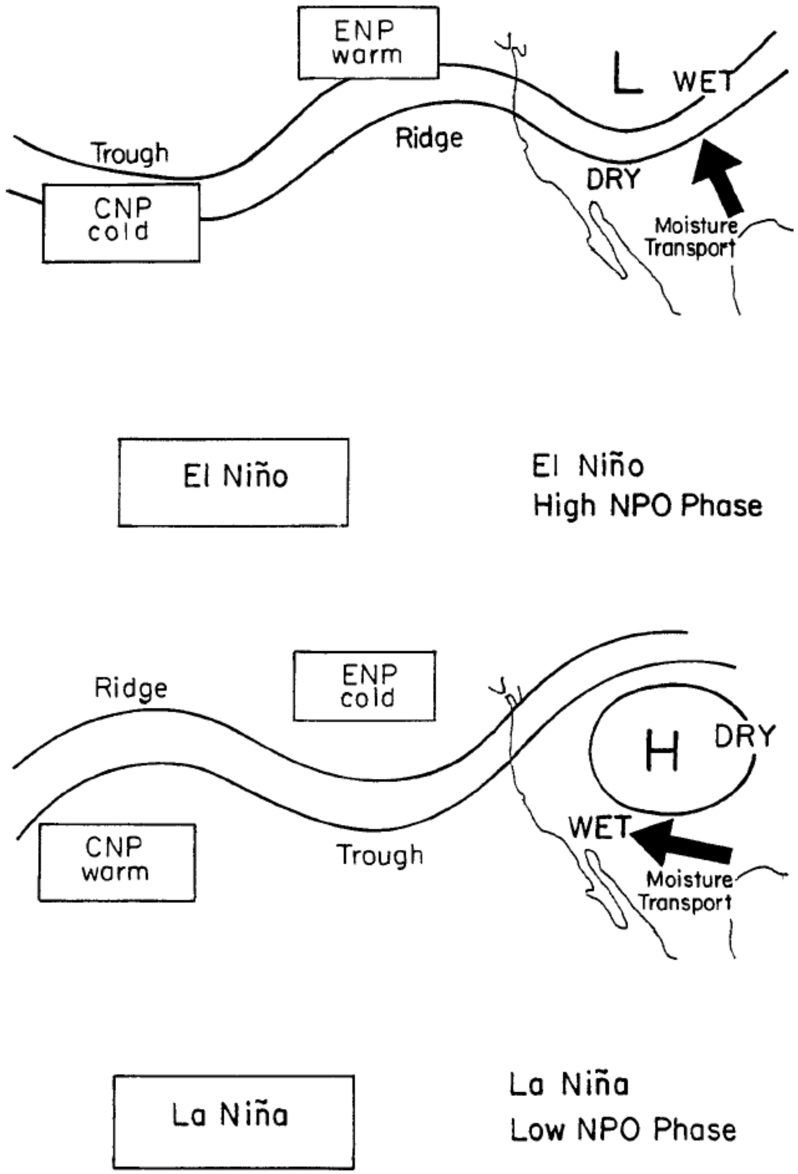
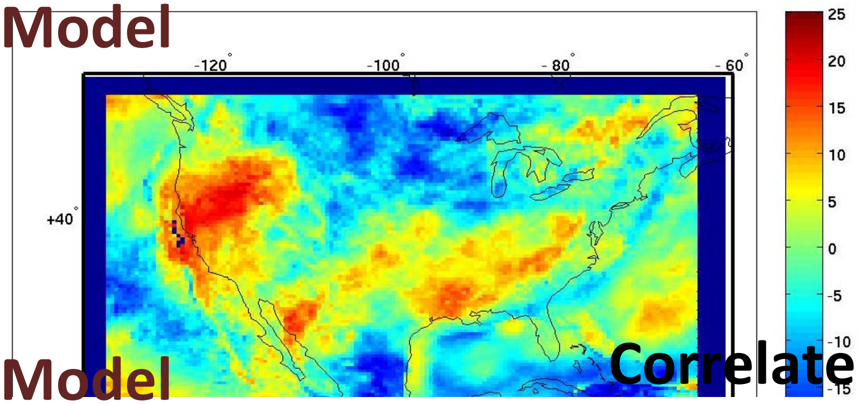


FIG. 14. Idealized relationship of monsoon ridge position and midlevel moisture transport to Pacific SSTs at monsoon onset.

Early summer teleconnection patterns (late June, early July)

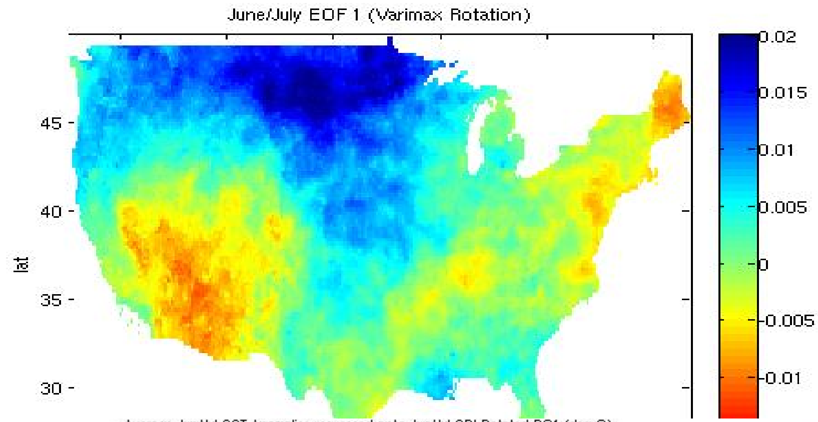
(Castro et al., 2001)

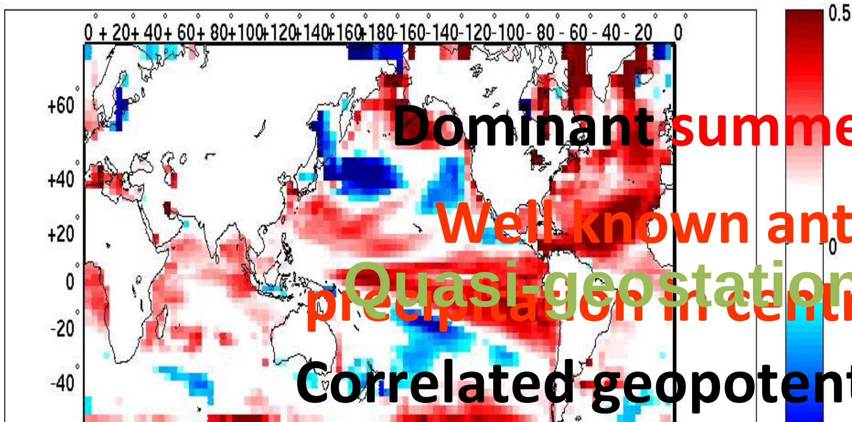
Model



Correlated SS

Model





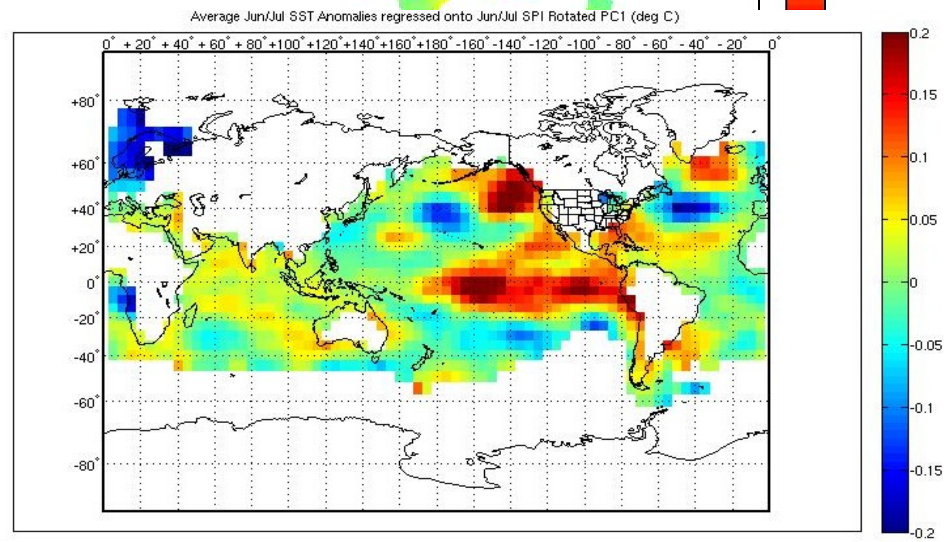
Dominant summer pr

Well known anticor

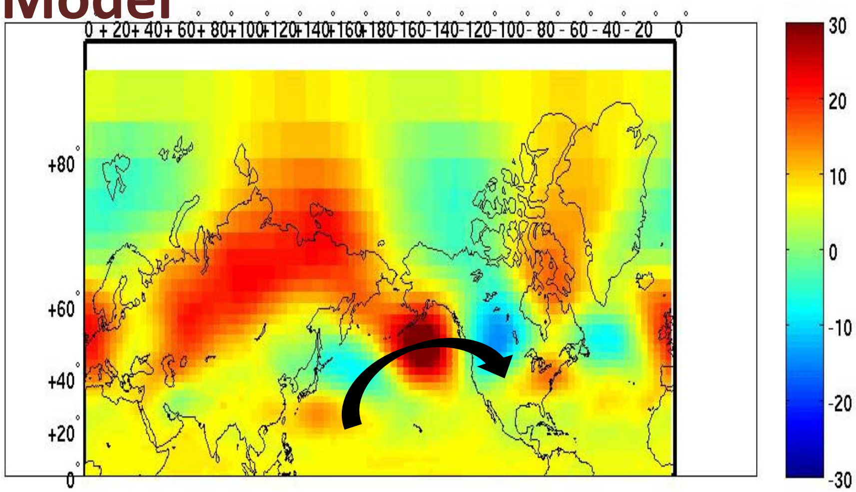
Quasi-geostationary

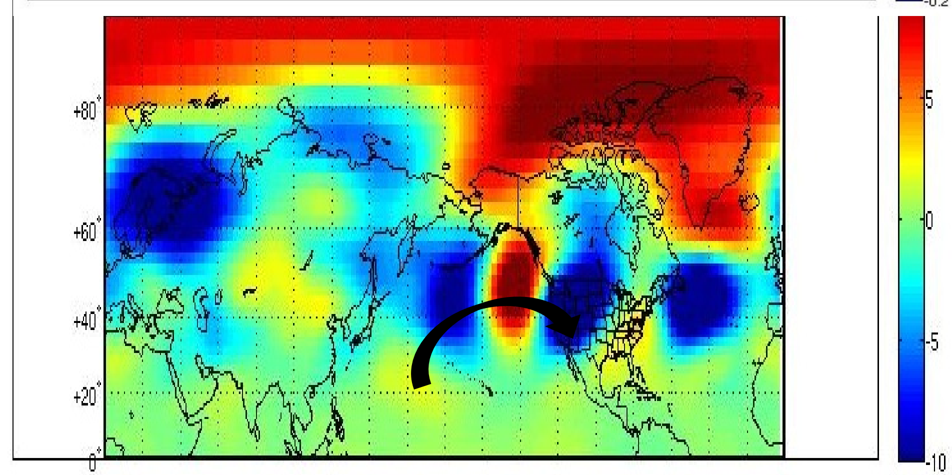
precipitation in central

Correlated geopotential



Model





RCM with dynamically downscaled GCM data is able to capture:

- Seasonal precipitation variability (winter and summer)
- Large-scale forcing corresponds to the dominant precipitation pattern
  - ENSO pattern
  - Stationary patterns in the atmospheric circulation both in winter and summer
    - Quasi-geostationary Rossby wave (different driving mechanisms for winter and summer)

The regional model is adding substantial value to the representation of the interannual variability of the driving global model.

Conclusions

1. The Reclamation statistically downscaled data has been used as atmospheric forcing for the VIC model

2. All three selected models show a decrease in streamflow and slowflow and variable precipitation and ET in the Salt/Verde.

3. Dynamical Downscaling of HADCM3 data has been finalized.

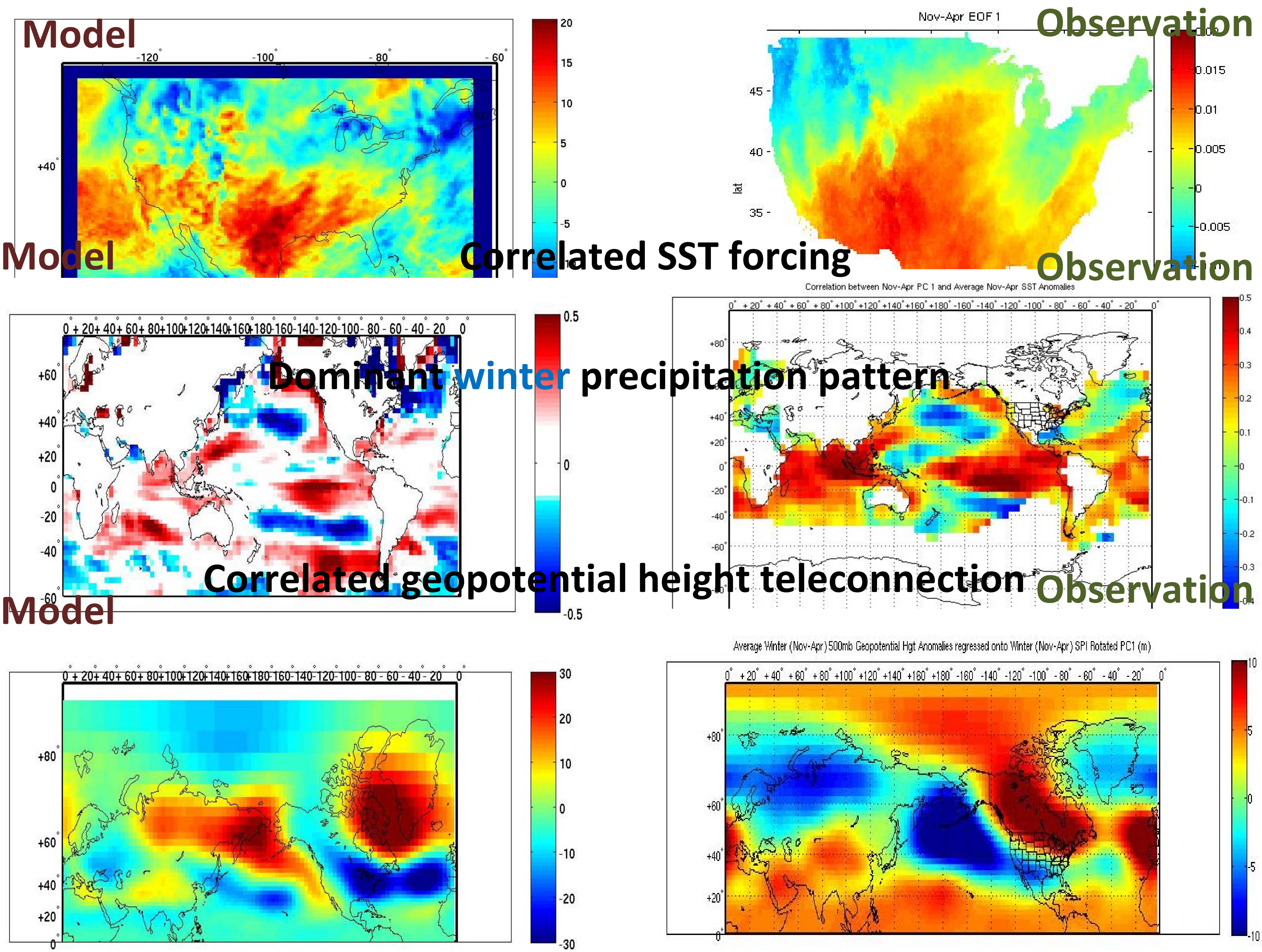
4. Climatological analyses show clear improvements when compared to raw GCM data.

Conclusions

5. In the dynamically downscaled WRF HADCM3 interannual variability is well captured for both summer and winter seasons.

Lessons Learned:

1. Obtaining the forcing data is NOT trivial, in this case we are fortunate that the NARCCAP effort is underway.
2. Probably most of the personnel time was spent modifying the data to be input into WRF. However, “nursing” the model also involves personnel time.
3. Pre-processing must be done in advance of model runs.
4. Forcing data is not perfect, some days have garbage.
5. We are still dealing with the issues of data sharing. These involve SIGNIFICANT volumes of data transfer.
6. We anticipate storage needs on the order of 100 TB for future simulations.



Model
Nov-Apr EOF 1
Observation
Dominant winter precipitation pattern
Model
Correlated SST forcing
Observation
Correlation between Nov-Apr PC 1 and Average Nov-Apr SST Anomalies
Correlated geopotential height teleconnection
Model
Observation
Average Winter (Nov-Apr) 500mb Geopotential Hgt Anomalies regressed onto Winter (Nov-Apr) SPI Rotated PC1 (m)